AI models for creditworthiness assessment

Ricardo Muñoz-Cancino[1]

[1]Ph.D. Student
Faculty of Physical and Mathematical Sciences
University of Chile

May 2022

Table of Contents

Table of Contents

What is credit risk?

The Basel Committe on Banking Supervision (2000) defines Credit risk as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms.

Why is it important?

For financial institutions:

- Credit Risk is acknowledged as one of the most significant risks a bank faces
- It is important to manage credit risk because if borrowers do not repay their loans, the lender loses money. And if this loss occurs on a large scale, it can affect the company's liquidity and even cause its bankruptcy.

Why is it important?

For the population:

- Access to credit is essential to support social mobility and financial success
- According to the world bank, 1.7 billion adults remain unbanked
- Being unbanked or underbanked presents the lack of credit history, meaning that people cannot obtain a credit no for being bad payers, but rather lack the attributes to be evaluated by traditional credit scoring models

How do banks measure the creditworthiness of a borrower?

- To determine the creditworthiness of a borrower, financial institutions have applied credit scoring for decades.
- The purpose is to estimate whether a customer will pay back the loan and avoid granting credit to people with a high probability of default.
- Credit Scoring uses personal information, banking data, and the payment history.

How do we improve the borrowers' creditworthiness assessment?

- Financial institutions, fintech, and researchers have worked in two main ways to improve the creditworthiness assessment: better algorithms or more data, specifically alternative data sources.

What will we see today?

A bit of both worlds, new algorithms, and alternative data sources. In particular, we will use graph data as an alternative data source.

What is graph data?

- We define graph data as that information that records the relationships or interactions among entities. In this way, a network corresponds to a group of nodes in which edges connect pairs of nodes.
- In this study, the nodes represent people or companies, and the edges represent the multiple kinds of interaction between them.
- We will refer to a network as a Social Network when nodes are people or companies, and edges denote any social interaction like friendship, acquaintances, neighbors, colleagues, or affiliation to the same group (Easley & Kleinberg 2010)

Why do we use graph data?

We are social individuals, generating and maintaining relationships with other individuals throughout our lives. Our friends do not seem like a random sample of the population, and they share our beliefs, opinions, hopes, hobbies, or mutual interests.
So it is logical to think that our relatives could help us in case of economic difficulties.

How do we extract knowledge from graphs?

We will use network representation learning:

How do we extract knowledge from graphs?

We will use network representation learning:

- Feature Engineering
- Network Embeddings
- Graph neural networks (GNN)

Table of Contents

Disclaimer

From now on, we will review the results of Muñoz-Cancino et al. (2021):

- *Muñoz-Cancino, R., Bravo, C., Ríos, S. A., and Graña, M. (2021). On the combination of graph data for assessing thin-file borrowers' creditworthiness. arXiv preprint arXiv:2111.13666.*

You can check the article for all the details.

Data Description

The information used in this research originates from a Latin American bank. The information provided by the financial institution to create networks originates from varied sources and can be cataloged as follows

- **[WeddNet]** Network of marriages
- **[TrxSNet]** Transactional services Network
- **[EnOwNet]** Enterprise's ownership Network
- **[PChNet]** Parents & Children Network
- **[EmpNet]** Employment Network

Feature Sets

- Borrower
- NodeStats
- EgoNet
- N2V
- GNN

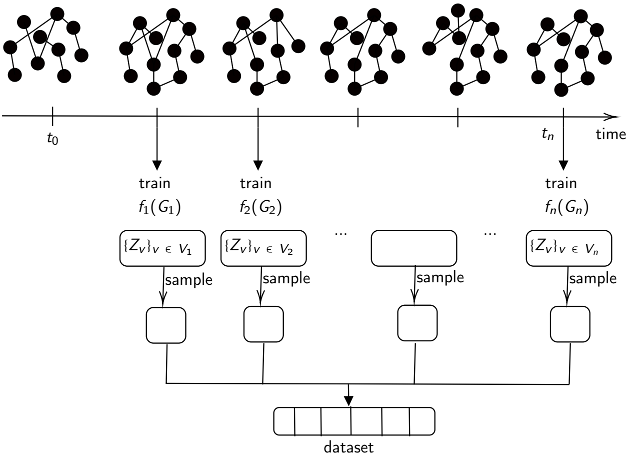

Figure: Node2Vec to Features

GNNs Features

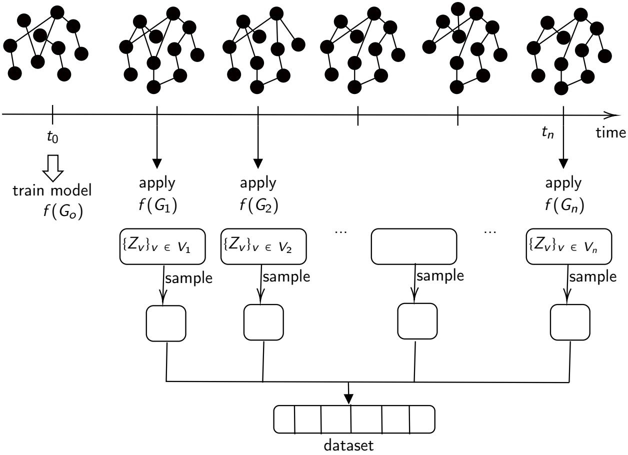

Figure: Graph Convolutional Networks and Graph Autoencoders to Features

Credit Scoring with Social Networks

- The credit scoring models are built with information about the financial system for 24 months.
- Target: A person or company is considered defaulter when it is 90 or more days past due within twelve months from observing him.

Table: Description of dataset

Scoring application	Model	Observations	# Features
Unbanked Application Scoring	Business Credit Score	29,044	687
	Personal Credit Score	192,942	1,283
Behavioral Scoring	Business Credit Score	931,910	687
	Personal Credit Score	1,978,664	1,283

Credit Scoring Performance

Table: Improvement in AUC relative to the benchmark model (mean and std), measured as $\frac{row_{AUC} - BenchScore_{AUC}}{BenchScore_{AUC}}$. We only report results when the equal performance hypothesis is rejected, with a confidence level of 95%; otherwise, we display *. The best performance in each column is shown in bold; more than one bold value indicates the hypothesis of equal performance between those models cannot be rejected.

Feature Set	Business Credit Score		Personal Credit Score	
	Application	Behavioral	Application	Behavioral
Borrower	*	0.58% ± 0.06%	1.45% ± 0.39%	0.95% ± 0.06%
Borrower + NodeStats	*	1.13% ± 0.12%	2.02% ± 0.49%	1.07% ± 0.06%
Borrower + EgoNet	**8.96**% ± 3.37%	2.33% ± 0.15%	2.31% ± 0.64%	1.25% ± 0.08%
Borrower + GNN,N2V	3.92% ± 2.03%	1.77% ± 0.13%	3.17% ± 0.55%	1.96% ± 0.04%
Borrower + NodeStats + EgoNet	**9.00**% ± 3.47%	2.37% ± 0.16%	2.39% ± 0.60%	1.32% ± 0.08%
Borrower + NodeStats + GNN,N2V	4.25% ± 1.84%	1.94% ± 0.16%	3.26% ± 0.48%	2.03% ± 0.05%
Borrower + NodeStats + EgoNet + GNN,N2V	**8.43**% ± 2.83%	**2.80**% ± 0.16%	**3.58**% ± 0.61%	**2.18**% ± 0.04%

The advantages of Graph Representation Learning Blending

Table: Graph Representation Learning blending performance. The performance enhancement of training a model using all graph representation learning methods (full: Borrower + NodeStats + EgoNet + GNN,N2V) is measured as the relative increase in AUC ($\frac{[full]_{AUC} - column_{AUC}}{column_{AUC}}$).

Scoring	Model	Feature Set			
		Borrower EgoNet	Borrower NodeStats EgoNet	Borrower GNN,N2V	Borrower NodeStats GNN,N2V
Application Scoring	Business Credit Score	*	*	4.33%	4.00%
	Personal Credit Score	1.23%	1.16%	0.39%	0.31%
Behavioral Scoring	Business Credit Score	0.47%	0.43%	1.02%	0.85%
	Personal Credit Score	0.92%	0.84%	0.22%	0.15%

Table of Contents

Conclusions

- We introduced a framework to combine traditional hand-engineered features with Graph Embeddings and Graph Neural Networks features. This framework produces a single score, facilitating its users to decide to approve or reject a credit.
- Our results are the first to validate and test graph data over both corporate and consumer lending, showing that the information from graphs has a different effect depending on the client under analysis, people, or companies.
- To the best of our knowledge, this is the first study that considers the credit behavior of an entire country, together with social networks that allow characterizing its entire population and consolidate multiple types of social and economic relationships: parental, marital, business ownership, employment, and transactional services.

Acknowledgments

This work would not have been accomplished without the financial support of CONICYT-PFCHA/DOCTORADO BECAS CHILE/2019-21190345.

THANK YOU!

If you have any questions, just write me an email at
rimunoz@uchile.cl

References I

Easley, D. & Kleinberg, J. (2010), *Networks, Crowds, and Markets: Reasoning About a Highly Connected World*, Cambridge University Press, USA.

Muñoz-Cancino, R., Bravo, C., Ríos, S. A. & Graña, M. (2021), 'On the combination of graph data for assessing thin-file borrowers' creditworthiness', *arXiv preprint arXiv:2111.13666* .

The Basel Committe on Banking Supervision (2000), 'Principles for the management of credit risk', *Basel Committee Publications* **75**.
URL: *https://www.bis.org/publ/bcbs75.pdf*